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Brief Papers

A novel Supervised Competitive Learning algorithm

Qun Dai*, Gang Song

College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China

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ABSTRACT

Competitive learning is a mechanism well-suited for the learning paradigm of regularity detection, and is typically an unsupervised learning mechanism. However, in this work, a novel Supervised Competitive Learning (SCL) algorithm is proposed for the generation of Multiple Classifier Systems (MCSs), which is substantially supervised. SCL algorithm seeks to strengthen simultaneously both the accuracy of and the diversity among the base classifiers in the MCSs, in a supervised and competitive manner. Our inspiration for the development of SCL algorithm comes from the modern education concept and those classical competitive learning algorithms intuitively. It is found through the experimental study of this work that, SCL algorithm effectively improves the classification and generalization performance of the constructed MCSs.

1. Introduction

Competition in neural networks means that, provided the input pattern, the processing elements in a neural network will compete for the "resources", such as the output [1–4]. For every input pattern, all the processing elements will generate an output. Only the "most desirable" output is adopted, and only the winning processing element is renovated. Competition is needed because competition produces specialism in the neural network, while specialism implies that, by competition, the processing elements are adapted and specialized for different regions of the pattern space. In many situations, resources are limited, so competition recreates these natural constraints in the environment [1–4].

In the past two decades, Multiple Classifier Systems (MCSs) have been well established as a research direction [5]. Intuitively, a critical factor to the successful construction of a MCS is that its base classifiers possess diversified performance [5]. Researchers have developed abundant algorithms to build a superior MCS by simultaneously exploring both the accuracy of the base classifiers and the diversity among them [5–15]. While in this work, we propose a novel Supervised Competitive Learning (SCL) algorithm for the generation of MCSs. Our SCL algorithm fundamentally differs from those classical competitive learning algorithms in that, SCL algorithm for the generation of MCSs is substantially supervised. And our SCL algorithm seeks to enhance both the accuracy of and the diversity among the base classifiers in a MCS at the same time, in a supervised and competitive manner.

The rest of this paper is organized as follows. In Section 2, the proposed Supervised Competitive Learning (SCL) algorithm for the generation of diversified MCSs is described in detail. Section 3 reviews the related researches about the diversity property of the MCSs and the diversity measures for the MCSs briefly. Section 4 reports results of the experimental study. Finally, conclusions are drawn in Section 4.2.

2. A novel Supervised Competitive Learning (SCL) algorithm for MCSs

2.1. Our main ideas about the proposed SCL algorithm for MCSs

In this work, we propose a novel SCL algorithm for the generation of diversified MCSs, which is substantially supervised. Our inspiration for the development of the SCL algorithm comes from the modern education concept and those classical competitive learning algorithms intuitively. Firstly, to train and build an excellent MCS is just as the talent cultivation. During the process of our pedagogical practices, it is reasonable and indispensable to teach groups of students in accordance of their aptitude and based on their special characteristics, so as to make the students give full play to their potential, make up for the deficiency of each student,

* Corresponding author. Tel.: +86 25 84593038; fax: +86 25 84498069.
E-mail address: daiqun@nuaa.edu.cn (Q. Dai).

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stimulate students' interest in learning, and help students to strengthen learning confidence, thus finally promoting students' all-round development.

Similarly, with the SCL algorithm, MCSs are constructed in a supervised and competitive manner, in accordance with their "aptitude", or rather, with their classification capability.

Secondly, our inspiration of SCL also comes from the rationale of those classical competitive learning algorithms. Competition mechanism is required in the build of MCSs since specialization of the base classifiers can be obtained from competition. In the context of MCS, specialization implies that, through competition, the base classifiers learn and specialize for different fields of the hypothesis space. Taking another look at it, specialization of individual base classifiers can be comprehended as a kind of specific implementation to the diversity of MCSs.

And similar to those classical competitive learning algorithms [1,16,17], in the context of MCS, resources are also restricted. Therefore the learning chances of the individual base classifiers are also restricted. The classifiers are demanded to compete with each other to acquire the opportunity to learn.

Analogous to the teaching method which teaches students in accordance with their aptitude, and those classical competitive learning algorithms, with our proposed SCL algorithm, we build our MCSs competitively, based upon their "aptitude", or rather, based upon their classification capability. Specifically, in the initialization stage, a set of base classifiers are initialized randomly. Next, in the preliminary training stage, the grounding of each base classifier is carried out with the whole training dataset for a certain number of preliminary training epochs. And then, in the competitive learning stage, all the base classifiers are trained competitively, namely, intensive training is carried out for the winner classifiers which stand out from the competition. In the end, after implementing the former three stages, the final testing stage is implemented, where the MCS is tested with the testing dataset.

Specifically about the implementation of the competitive learning stage, after the preliminary training stage has been completed, for each training sample, the classification capability of each base classifier towards the sample is evaluated in a supervised manner. Those base classifiers with sufficient classification capability to one training sample are regarded as "winners" in the competition for that specific sample. The strategy that "the winner takes all" is also employed in our SCL algorithm. Only those winning classifiers in the competition for one specific training sample will have the chance to learn it, or to be trained with it. Conversely, failing classifiers do not have opportunity to learn. They even do not have the chance to forget what they have already learned.

As a satisfactory result, we are pleasantly surprised that the proposed SCL algorithm effectively boosts the diversity of the generated MCS, and consequently, significantly improves the pattern classification performance of the constructed MCS. This satisfactory result might due to the reason that the property of diversity plays an important role in a MCS. The performance of a MCS not only depends on the power of the individual classifiers in the system, but also relies on the independence among them [18,19].

The effectiveness of the SCL algorithm can be properly explained as it enhances simultaneously both the power of individual classifiers and the diversity among them. Or it can be explained as the SCL algorithm effectively enhances the "beneficial diversity" among the classifiers in the MCS. While the term "beneficial diversity" here can be comprehended as the diversity of a MCS which can truly improve its classification performance. As pointed out by Kuncheval that, diversity is generally beneficial but it is not a substitute for accuracy [19]. Therefore, the key to the classification performance of a MCS is its "beneficial diversity".

In the preliminary training stage of the SCL algorithm, fundamental training to all the constituent classifiers is performed, laying a solid foundation for the recognition capability of the entire MCS, and for the successful implementation of the following competitive learning stage. And in its competitive learning stage, selective reinforcement learning is performed to those winners in the competition, which, at one time, effectively boosts the power of each individual classifiers and the diversity among them. In fact, the competitive learning stage of SCL algorithm can be understood as a final refinement and reinforcement to the MCS, which is indispensable to the further improvement of its classification performance.

Besides, in its effective enhancement to the diversity and classification performance of the generated MCS, the SCL algorithm avoids the implementation of ensemble selection. Although the paradigm of ensemble selection is very influential in the research field of ensemble learning [20–33], however, to develop an ensemble selection algorithm with superior performance is still a rather difficult task. In actual fact, the problem of ensemble selection has proven to be an NP-complete problem [34,35].

Moreover, although ensemble selection can reduce memory requirements and computational costs, improving the efficiency of decision making, a noteworthy weakness of almost all the existing ensemble selection algorithms lies in that, they curtly abandon all of the classifiers which are not selected into the pruned ensemble, resulting in a waste of useful resource and information. Everything has its two sides – positive and negative. From the above point of view, it could be said that SCL algorithm is superior to those ensemble selection algorithms in these respects.

Our SCL algorithm belongs to the kind of methods which manipulate the training data employed. Since naturally, if we competitively determine the winning classifiers to be trained with the specific training sample, conversely, different base classifiers will be trained with different training data in the competitive learning stage. And moreover, according to the taxonomy drawn by the authors in [36], our algorithm belongs to those methods which vary the set of hypotheses that are accessible by the MCSs.

As for whether our SCL algorithm belongs to explicit or implicit diversity methods, we might say that the algorithm falls in between them. Since although our algorithm is somewhat similar to Bagging [6], however, Bagging randomly samples the training patterns to produce different training sets for each member network, while our algorithm competitively, instead of randomly, selects subset of classifiers for each training sample. And although our algorithm is also similar to Boosting [8] in some ways, however, Boosting [8] method directly and explicitly manipulates the training data distributions to ensure some form of diversity in MCSs, which is fundamentally different from our algorithm. To be exact, our SCL algorithm is a kind of heuristic diversity method. The formal description of the proposed SCL algorithm for MCS is given out in the following sections.

2.2. The algorithm description of the proposed SCL algorithm for MCSs

2.2.1. The initialization of our MCSs with ICBP as the base model

For the sake of originality, effectiveness, ease of implementation and simplicity, we adopt Improved Circular Back-Propagation (ICBP) neural network model, proposed in one of our previous works [37], as the base classifier in our MCS, while our proposed SCL algorithm can be generalized to MCSs with any other types of base learning models very directly and easily. The initialization of our MCSs with ICBP as base model is realized just as the initialization of the n-Bits Binary Coding ICBP Ensemble System (nBBC-ICBP-ES) [15]. For the details about ICBP network model and nBBC-ICBP-ES, please refer to our published works [37,15].